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ORIGINAL PAPER

Forest Road Detection Using LiDAR Data

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Abstract: We developed a three-step classification approach for forest road extraction utilizing LiDAR data. The first step employed the IDW method to interpolate LiDAR point data (first and last pulses) to achieve DSM, DTM and DNTM layers (at 1 m resolution). For this interpolation RMSE was 0.19 m. In the second step, the Support Vector Machine (SVM) was employed to classify the LiDAR data into two classes, road and non-road. For this classification, SVM indicated the merged distance layer with intensity data and yielded better identification of the road position. Assessments of the obtained results showed 63% correctness, 75% completeness and 52% quality of classification. In the next step, road edges were defined in the LiDAR-extracted layers, enabling accurate digitizing of the centerline location. More than 95% of the LiDAR-derived road was digitized within 1.3 m to the field surveyed normal. The proposed approach can provide thorough and accurate road inventory data to support forest management.

Keywords: forest road, LiDAR, SVM, IDW method

Introduction

Because forest roads are important in forest management, it is indispensable to have a detailed map of every forest road for providing corridors for travel, recreation and education, infrastructure for fire protection and transport of forest products (White et al. 2010). Roads are also an important data layer in Geographical Information Systems (GIS) (Song and Civco 2004). Recent research on automatic road extraction is mainly motivated by the importance of GIS and the need for data acquisition and updated procedures (Hinz and Baumgartner 2003). Because of its low cost, surveying by GPS is currently the most suitable method for updating information of Iran forest roads (Abdi et al. 2012) but the method is usually time-consuming and inaccurate. Concerns regarding the use of GPS in forests include problems such as availability of satellite signals under a forest canopy and satellite characteristics (Rodriguez-Perez et al. 2007).

Automated road extraction using remote sensing data can save time and labor costs in updating a forest road database. Mapping the land surface using an airborne Light Detection and Ranging (LiDAR) system is the most accurate method (Gallay et al. 2012). This technology can be acquired with high frequency and accuracy in a short time (Baltsavias 1999). LiDAR is a reliable technique for collecting elevation data of several surface levels depending on the penetration of the laser beam to the ground. These data on elevation can be used to generate a Digital Elevation Model (DEM), and the recorded intensity of the backscattered laser beam can be used for classification of surface objects. In vegetated areas, the first returns generally correspond to the upper landscape canopy level (e.g., vegetation tops) and the last returns correspond to the terrain surface. The first returns are used to generate Digital Surface Models (DSM), while the last returns are used for generation of Digital Terrain Models (DTM) (Gallay et al. 2012).

DEM data are commonly in raster format; they are created using point files and can be interpolated using many different techniques. The techniques used to create DEMs range from simple (e.g., nearest neighbor) to complex (e.g., kriging) gridding routines and they can create slightly different surface types.

The most common types are surfaces created by the TIN or the Inverse Distance Weighted (IDW) routines. The method most appropriate to interpolation depends on the desired use of the DEM and the data. The IDW function should be used when the set of points is dense enough to capture the extent of local surface variations needed for analysis (Liu 2008). The IDW, using a linear-weighted combination set of sample points, calculates cell values. The assigned cell weight is a function of the distance of

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the input point from the output cell location. The greater the distance the less influence of the cell on the output value.

Detailed background on LiDAR can be found in Baltsavias (1999) and Pfeifer and Briese (2007). The classification of LiDAR data into objects such as road, tree and building in a forest area has been a challenging task in remote sensing studies (White et al. 2010; Feret and Asner 2012; Bandara et al. 2011). Several road extraction methods (e.g., maximum likelihood, neural networks and decision tree classifiers) have been proposed for classifying LiDAR data. Boggess (1993) used a classification method that incorporated texture and neural networks in classification of roads and other features from Landsat TM imagery but obtained numerous false-inclusions. Roberts et al. (2001) developed a spectral mixture library using hyperspectral images to extract roads, but the use of spectral information alone does not capture the spatial properties of the curvilinear features of such images. White et al. (2012) used a LiDAR-derived DEM to map characteristics of forest roads located beneath a dense forest canopy. The position, gradient, and total length of a forest haul-road were accurately extracted using a 1-m DEM.

Until recently, Support Vector Machine (SVM) was a popular approach for the classification of data used to extract roads (Gomez et al. 2010; Matkan et al. 2009).

The SVM classification technique has been increasingly applied to classification of airborne imagery (Camps-Valls et al. 2004; Melgani et al. 2004), where its higher accuracy compared to traditional techniques stems from its lower sensitivity to high dimensionality (Bazi and Melgani 2006). SVM is based on the statistical theory of learning, developed by Vapnik in 1998 (Cortes and Vapnik 1995). This theory provides a set of principles to be followed in order to find classifiers with good generalization, which is defined as the ability to correctly predict the class of new data in the same area where learning has occurred (Premebida et al. 2009).

Song and Civco (2004) used a SVM to extract roads by classifying them using LiDAR and obtained fine accuracy for classifying rural and urban roads. Gomez et al. (2010) compared the analysis of SVM and Mahalanobis algorithms for road extraction from high resolution data. The SVM algorithm was superior to Mahalanobis distance and LiDAR was introduced into the improved classification process.

The purpose of this study was to determine the suitability of LiDAR for extraction of forest roads. We classified LiDAR data using the SVM algorithm to extract a forest road and we evaluated the results. The paper is arranged as follows:

First, the SVM used for classification is described. Second, image segmentation used for shape extraction is introduced. Third, an experiment showing the proposed approach to extract roads using Ikonos images is described. Finally, we offer our discussion and conclusions.

Our objectives were to assess the accuracy of extraction of a forest road from LiDAR terrain data and compare the results with conventional centerline surveying. The road position was evaluated by the following criteria: (1) classification; determine the percentage of the road area that could be identified with the LiDAR data, (2) positional accuracy; determine the 95th percentile horizontal distance separating the LiDAR-derived and field-surveyed centerline.

Methods

Study area and data sources

The geographic setting for this study is a part of the Hyrcanian Forests in Golestan Province, Iran. The topography of the study area is steep and rugged with elevations ranging from 290 to 720 m and ground surface slopes exceeding 3% and up to 65% in some areas. The forest road was built in 1990 and used to access the Shastkola forest for timber harvest, forest protection, field research and management. The average width of the road surface was 3.5 m. Some of the road was hidden under the forest canopy, which covered 40%–100% of the road and averaged 80% coverage.

Airborne LiDAR data were collected by the National Geographical Organization of Iran (NGO), using a sensor mounted to a fixed-wing aircraft. The survey was conducted in October 2011 and LiDAR data were included in the first and last returns of the distance and intensity data, the average density of the points on the surface being 4 points per square meter.

Two vector layers, one of 87 survey control points, with 0.08 m accuracy horizontally, and another, a road network (line format) from previous studies in the same study area, was used to assess the newly extracted road.

Preprocessing and preparation layers

Random errors in the original LiDAR data can be caused by instruments such as cameras, GPS or non-surface features such as birds (Huising and Gomes-Pereira 1998). Consequently, to develop an accurate DEM, non-ground points must be removed prior to interpolation to a raster DEM (Shan and Sampath 2005; Zhang and Whitman 2005; Axelsson 1999). In our data, there were some LiDAR points with errors on cloud points, these points elevated the values unreasonably and were removed during preprocessing following Meng et al. (2009). One important decision to be made prior to ground filtering is the selection of the first or last returns of LiDAR for ground filtering (Hyyppa et al. 2003; Silvan-Cardenas et al. 2006). We selected the last return because the last pulses reach deeper in vegetated areas, and hence, the last ones are closer to the ground surface (Kraus and Rieger 1999; Okagawa 2001). These points from distance LiDAR data were removed and Eq. 1 was used:

$$\text{First pulse} - \text{Last pulse} > T \quad (1)$$

Based on Eq. 1, the difference between the first and the last pulse will not be less than a certain threshold; if it be less than T, that point is removed.

T was calculated from Eq. 2, σ is the error in measuring the elevation in LiDAR data:

$$T \geq \sqrt{\sigma^2 \text{First Pulse} + \sigma^2 \text{Last Pulse}} \quad (2)$$

Then, for recalculating the removed points, the IDW interpolation method was used, it being an interpolated method for calculation of the values assigned to unknown points in a set of points with a weighted average of the values available at the known points. In the next step, a Digital Terrain Model (DTM) and a Digital Surface Model (DSM) were generated. The last pulse is reflected from the ground surface, a fact important in a forested area, so the DTM was developed from the last pulse (Reutebuch et al. 2003). The DSM was developed from the first pulse data, which are reflected from the object level. To delete the topographic effect for road detection, the Digital Non-Terrain Model (DNTM) was used (Matkan et al. 2009). A DNTM layer was created from Eq. 3:

$$\text{DNTM} = \text{DSM} - \text{DTM} \quad (3)$$

Support Vector Machine classification and assessments

A Support Vector Machine (SVM) is basically a statistical linear learning machine based on the principle of optimal separation of classes (Watanachaturaporn 2005). SVM can identify a linear separation of the most favorable classes, provided the data are linearly separable. In this method, the training samples, describing the edges of the class, are used to delineate the two classes by fitting an optimal separating hyperplane. In the next step, the LiDAR intensity data were classified using SVM. Then, LiDAR distance data were used in the classification to remove the pixels that had radiometric values similar to the road surface pixels other than road pixels.

Assessment of the extracted road data was carried out by comparing the automatically extracted road centerlines to the manually plotted road axes used as reference data. Both data sets are given in the vector representation. Two steps were considered for the evaluation: (1) calculation of the number of extracted primitive roads using SVM algorithm that are matched to the number of reference network, and (2) calculation of quality measures (Wiedemann 2003). In the first step, the roads in both data sets were fragmented into short pieces of equal length. Then, a buffer of constant predefined width (3.5 m) was constructed around the reference road data. The parts of the extracted data within the buffer were considered matched if the difference of the direction between the reference road data and the part to be matched did not exceed a given threshold. This difference was derived directly from the vector representations of both roads. Following the notation of Bazi and Melgani (2006) and Baltsavias (1999), the matched extracted data were denoted as the true positive with length TP, emphasizing the fact that the extraction algorithm had indeed found a road. The unmatched extracted data were denoted as false positives with length FP.

In the second step, matching was performed the other way around. The buffer was constructed around the extracted road data, and the parts of the reference data lying in the buffer and fulfilling the direction constraint were considered matched. In cases of low redundancy their length was approximated by TP. The unmatched reference data were denoted as false negatives with length FN (Wiedemann et al. 1998). For comparison purposes, the road extraction was classified as TP, FN or FP on a pixel by pixel basis.

The definitions of the quality measures are presented in the following (defined by Wiedemann et al. 1998):

Completeness is the ratio of the records correctly extracted to the total number of relevant records within the ground-truth data (Eq. 4):

$$\text{Completeness} = \frac{TP}{TP+FN}, \quad \text{Completeness} \in [0, 1] \quad (4)$$

Correctness is the ratio of the number of relevant records extracted to the total number of relevant and irrelevant records retrieved (Eq. 5):

$$\text{Correctness} = \frac{TP}{TP+FP}, \quad \text{Correctness} \in [0, 1] \quad (5)$$

Quality is a measure of the goodness of the final result. It takes into account the completeness of the extracted data as well as their correctness, as defined in Eq. 6:

$$\text{Quality} = \frac{TP}{TP+FP+FN}, \quad \text{Quality} \in [0, 1] \quad (6)$$

Comparison of extracted road centerline with field-surveyed centerline

The position of the LiDAR-derived centerline to the field-surveyed centerline location was compared using a simple method described by Goodchild and Hunter (1997). We extracted 117 field-surveyed checkpoints for the exact location. This approach compared a linear feature of high accuracy to a feature of lower accuracy, and determined the percentage of the low accuracy line that fell within a specified horizontal distance normal to the high accuracy line. The method was used to answer the following question: what percentage of the digitized forest road fell within (x) meters normal to the surveyed road centerline? The overall positional accuracy was measured by 95% of the test line width.

Results and Discussion

In this study, precision of the LiDAR data for height was 15 cm, so we used Eq. 2:

$$T \geq \sqrt{15^2 + 15^2} = 21 \text{ cm} \quad (7)$$

where, T was chosen as the threshold, considering this threshold would remove 585 false points from the LiDAR cloud points.

The removed points were less than 10% of the total points as calculated by the IDW interpolation method.

The outcomes of the IDW displayed next, the interpolation accuracy for IDW interpolator and 1-meter cell resolution was assessed using the RMSE statistic:

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{i=1}^{n}\left(z_{i(\mathrm{interpolated})} - z_{i(\mathrm{truth})}\right)^2}{N}} = 0.19 \text{ m} \qquad (8)$$

The size of a grid cell is commonly referred to as the grid cell's resolution, with a smaller grid cell indicating a higher resolution. A grid cell resolution must be selected as part of the interpolation process; each interpolation technique is implemented using a user-selected grid cell resolution (Wechsler 2007). The output for the generated DTM layer from the last pulse after IDW interpolation, DSM and DNTM are displayed in Fig. 1.

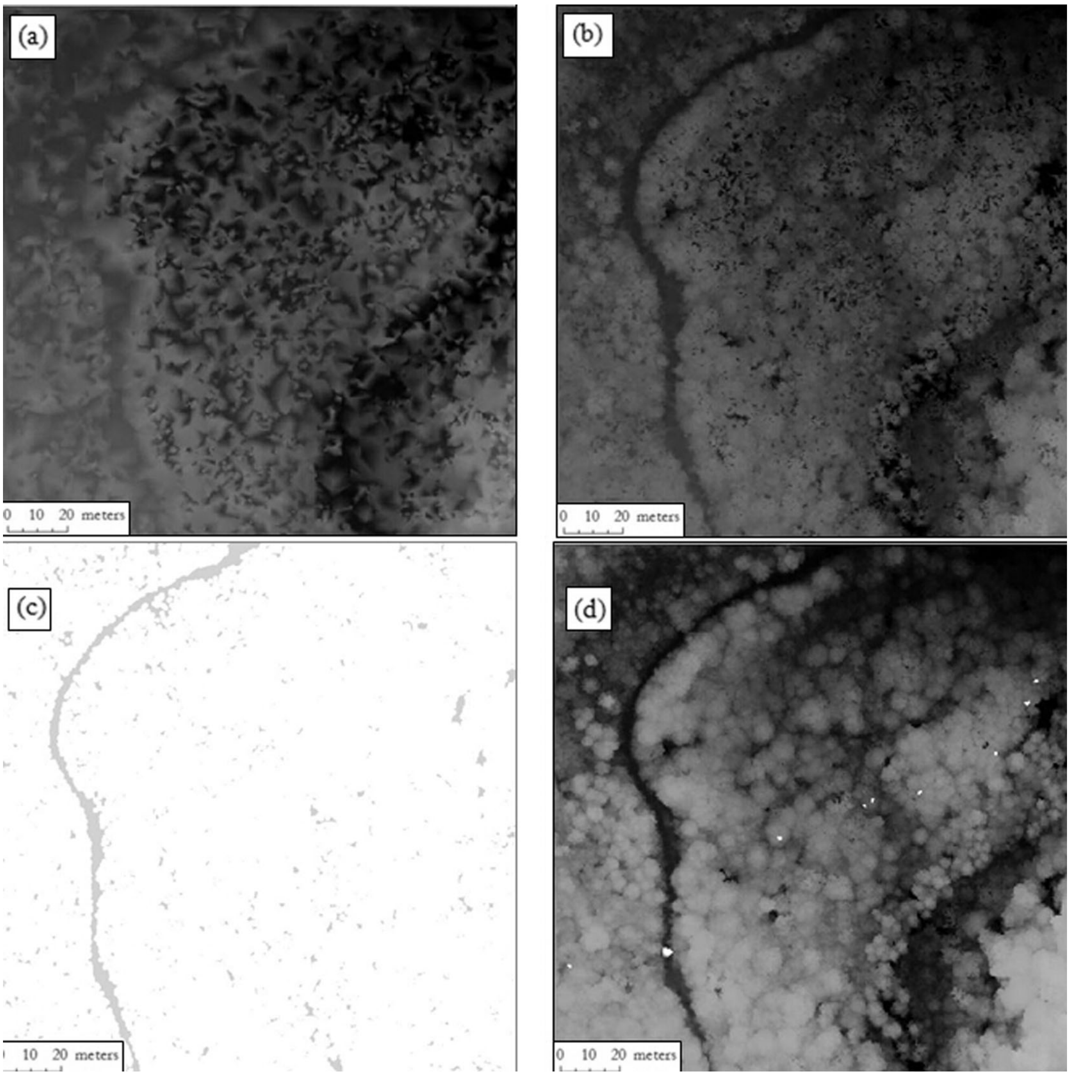

Fig. 1: (a) DTM; (b) DSM; (c) DNTM; (d) Intensity data

Evaluation of the results of the interpolation method showed that IDW was a suitable method for interpolating LiDAR data, as reported by Ali (2004), Blaschke (2004) and Podobnikar (2005), i.e., the IDW method performs well, if the density of sampling data is high. LiDAR data have high sampling density, so IDW is a suitable interpolator for a DEM generatws from LiDAR data (Liu et al. 2007). On the basis of the point density (four points per square meter), the RMS of IDW method was appropriate for this study.

In the next step, the LiDAR intensity data as well as the merged data (intensity data and DNTM layer) were classified by SVM. Each pixel of the extracted road data in the previous stage was classified as true positive (TP), false negative (FN) or false positive (FP). The results are shown in Table 1.

Table 1: Support Vector Machine (SVM) classification matrix

	TP	FP	FN
Intensity data	28403	38114	19758
Merged data	36145	21209	12003

The road edges were well-defined in the LiDAR-extract layers and enabled an accurate digitizing of the centerline location. More than 95% of the LiDAR-derived road was digitized within 1.3 m of the normal field-surveyed centerline. The remaining five percent of the road length was located further than 1.3 m from the surveyed centerline, though the maximum separation between the field-surveyed and digitized centerline did not exceed 1.7 m. Part of this survey and the digitized road centerline is shown in Fig. 2.

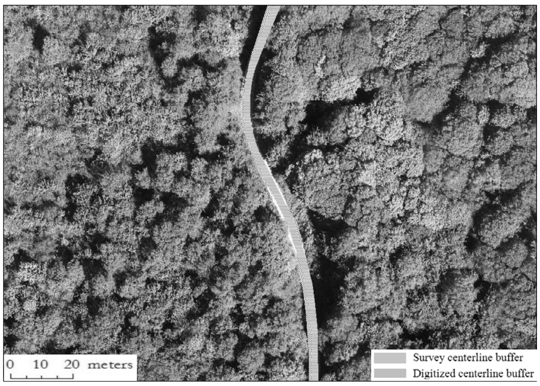

Fig. 2: Field surveyed centerline buffer (green) and digitized centerline buffer (pink)

Completeness, correctness, and quality values calculated for the extracted road are listed in Table 2. We developed the SVM approach for road extraction based on classification. It was easy to operate in road extraction in this experiment, regardless of the results.

Table 2. Assessments of SVM classification

	Correctness	Completeness	Quality
Intensity data	42.70%	58.97%	32.92%
Merged data	63.02%	75.07%	52.11%

Road position is an important inventory parameter for forest management assessment. Road position can be obtained accurately and efficiently using high-resolution LiDAR data, which reduces the need for field-based surveys for this basic parameter. Greater opportunities now exist for broad-scale analyses which incorporate thorough and accurate measurements of forest road systems. LiDAR-derived road data can address gaps that exist in current data sources, especially for forested areas, and represent a valuable tool to assess forest roads at scales not previously feasible (White et al. 2010).

Conclusions

Forest road maps can serve a variety of purposes for forest managers. Producing updated road maps is among the most valuable and easily attained products of LiDAR data analysis. In this study, forest roads were identified and some roads extracted, particularly those that did not have a pronounced topographic cross-sections or were difficult to identify using LiDAR surface grids, such as those used by White et al. (2010). In general, despite the large number of automated software designs, road extraction typically remains a manual process in the field of forestry (Doucette et al. 2009).

In this study, a simple and relatively efficient method was provided for extraction of forest road features, although we identified some disadvantages. If automated road extraction were conducted for mapping larger areas, despite additional training to achieve improvements in efficiency, these techniques might yield substantial time-savings (White et al. 2010; Doucette et al. 2009). With LiDAR extract layers, forest managers can identify terrain conditions before entering the field, aiding the initial planning and wood transport layout.

Access to accurate maps of forest roads can provide forest managers with good agreement between initial plans and actual field conditions, e.g., forest road maps can be used for harvest planning operations or for wildfire preparedness.

The ability to extract road maps in forested areas can be substantially improved by the proposed method as compared to use of traditional data sources. In addition to describing road features, road characteristics measured using LiDAR methods were highly accurate.

The ±1.3 m positional accuracy for road features is a substantial improvement compared to the accuracy (±10 m) of traditional data sources used to plot roads on the 1:25,000 topographic maps in IRAN. A similar level of positional accuracy of one to two meters for an extracted road centerline was reported by Rieger et al. (1999) and White et al. (2010). The level of positional accuracy needed for GIS datasets varies substantially with their intended use. For analysis conducted at the scale of this study, a simple criterion for horizontal accuracy was that the digitized centerline must lie within the width of the actual road bed. The maximum distance between the field-survey centerline and the digitized line was 1.3 m and was essentially one-half of the width of the Shastklola road.

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